International Journal of Advances in Electrical Engineering

E-ISSN: 2708-4582
P-ISSN: 2708-4574
Impact Factor (RJIF): 5.6
IJAEE 2025; 6(2): 01-06

www.electricaltechjournal.com
Received: 05-05-2025
Accepted: 15-06-2025

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Optimal siting of wind turbines using the grey wolf optimization algorithm

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Abstract
Optimal siting of wind turbines is one of the key issues in the field of clean and sustainable energy production, attracting the attention of engineers and researchers aiming to improve their performance and efficiency. In this regard, the use of metaheuristic algorithms has been proposed as powerful and effective methods for the optimal placement of wind turbines. In this study, we investigate and optimize the siting of wind turbines using the Grey Wolf Optimization (GWO) algorithm. The main goal of this research is to increase the efficiency of energy production and reduce inter-turbine interference by selecting optimal installation locations. Initially, the turbines were assumed to be positioned regularly and at equal distances. Then, using the Grey Wolf Optimization algorithm, the optimal siting of turbines was performed based on two main criteria: maximizing the produced energy and minimizing interference between turbines. Google Colab was used for simulating and executing the algorithm. The results of the algorithm's implementation showed that the Grey Wolf Optimization algorithm was able to effectively identify the optimal turbine locations. Analysis of the results indicated that with an increase in the number of iterations, the amount of produced energy significantly increased, while interference between turbines was minimized. This demonstrates the efficiency and effectiveness of the Grey Wolf Optimization algorithm in solving the problem of optimal siting of wind turbines. In general, it can be concluded that using the Grey Wolf Optimization algorithm for optimal wind turbine siting is a suitable and efficient approach that can contribute to improved energy efficiency and reduced interference. These results can pave the way for further studies and research in the application of optimization methods in the field of renewable energy.

Keywords: Wind turbines, grey wolf optimization algorithm, optimal siting, metaheuristic algorithms

Introduction

Optimal siting of wind turbines, as one of the most important topics in the field of renewable energy, has attracted the attention of many researchers and industry professionals. Given the growing demand for clean energy and the depletion of fossil fuel resources, utilizing wind energy as one of the main sources of renewable energy has gained special importance. Selecting a suitable location for installing wind turbines plays a significant role in increasing energy production and reducing the costs associated with installation and maintenance. Various methods have been proposed for wind turbine siting, including analytical, numerical, and artificial intelligence-based approaches. However, many of these methods have failed to achieve optimal and acceptable results due to environmental complexities and inter-turbine interferences. In addition, insufficient attention to critical criteria such as interference between turbines and energy production in these methods has led to reduced efficiency and performance of wind systems. In this chapter, a novel and efficient method for optimal wind turbine siting is presented, which, through the combination of artificial intelligence and optimization algorithms, aims to maximize energy production and minimize inter-turbine interference. This method utilizes environmental data and real-world information to find the best possible locations for installing turbines, thereby improving the efficiency of wind systems. In general, the main innovation of this research is the use of the Grey Wolf Optimization (GWO) algorithm for optimizing wind turbine siting. The use of the GWO algorithm in this context, due to its unique features in exploring the solution space and finding both local and global optima, can offer better results compared to traditional methods. This algorithm, inspired by the hunting behavior of grey wolves, has a strong ability to converge toward optimal solutions and can provide a suitable combination of maximum energy production and reduced interference between turbines. This leads to more efficient turbine placement in the area and overall improved system performance.

Steps of the Proposed Method

As stated earlier, the main innovation in this study is the application of the Grey Wolf Optimization algorithm for optimizing the siting of wind turbines. This algorithm, inspired by the hunting behavior of grey wolves, is used for the first time in this research for wind turbine siting optimization. The use of the Grey Wolf Optimization algorithm in the wind energy domain, due to its simple structure and high efficiency in finding local and global optima, makes it a suitable choice for this complex problem. Metaheuristic algorithms such as Grey Wolf Optimization, due to their broad search capability in the solution space and their ability to avoid being trapped in local optima, can significantly improve optimization results. This research was conducted with the aim of combining two main objectives: maximizing energy production and minimizing interference between turbines. These objectives, which are typically in conflict with each other, have been optimally balanced using the Grey Wolf Optimization algorithm. By adopting a multi-objective approach, the GWO algorithm has created an optimal balance between conflicting goals and achieved results that are difficult to obtain using traditional methods. The turbines were initially deployed in a manner that evenly covered the entire area. This initialization contributed to improving the algorithm's performance in subsequent optimization steps.

Objective Function of the Algorithm: The objective function in this problem includes two main criteria: interference and generated energy. The following provides an explanation of each of these criteria:

1: Interference

Interference between turbines is considered as one of the criteria, and it is defined as follows:

$$Interference = \sum_{i=1}^{N} \sum\nolimits_{j=i+1}^{N} \left(\min_{distance} - distance_{ij} \right)^2$$

In this formula

- N is the total number of turbines.
- $distance_{(ij)}$ is the distance between the *i*th and *j*th turbine.
- Min_distance is the minimum desired distance to avoid interference (here it is assumed that the minimum distance is 10 units).

Interference is calculated based on the distance between each pair of turbines when the distance between them is less than the minimum distance. The amount of interference increases. As a result, the goal of this part of the objective function is to choose the distance between each pair of turbines in a way that minimizes the total interference.

2: Generated Energy

The energy generated by the turbines is calculated based on the wind speed and the locations of the turbines. The generated energy is defined as follows:

$$Energy\ Production = \sum_{i=1}^{N} \frac{1}{2} AV_{p_i^3}$$

In this formula

- N: Number of turbines.
- P: Air density (assumed to be constant here).
- A: Wind capture area of turbine blades.
- V_i is the wind speed for the ith turbine.

The purpose of calculating the generated energy is to compute the maximum amount of energy generated by the turbines placed in optimal locations. Wind speed may vary at different points; therefore, turbines located in areas with higher wind speeds generate more energy. The main objective of the objective function in this algorithm is to optimize the placement of turbines in such a way that the interference between them is minimized while the generated energy is maximized. These two criteria are considered in combination to achieve better results for turbine placement.

3: Evaluation Metrics

In this section, we will introduce the evaluation metrics used to assess the proposed model. The interference between turbines is considered as one of the evaluation criteria, which is defined as follows:

$$Interference = \sum_{i=1}^{N} \sum\nolimits_{j=i+1}^{N} (\min\_distance - distance_{ij})^2$$

The energy production criterion of the turbines is also calculated based on wind speed and the location of the turbines. The energy production criterion is defined as follows:

$$Energy\ Production = \sum_{i=1}^{N} \frac{1}{2} AV_{p_i^3}$$

4: Analysis and Evaluation of Results

In this section, the results obtained from the implementation of the Grey Wolf Optimization (GWO) algorithm for the optimal placement of wind turbines are analyzed. This analysis includes evaluating the performance of the algorithm in optimizing turbine positions in order to maximize energy production and reduce interference between turbines.

As stated in the proposed method chapter, the first step is to simulate the environment for placing the turbines. The location environment is considered as a rectangular area with dimensions of 60 × 20 units. The number of wind turbines is set to 10. Moreover, the initial positions of the turbines are arranged in such a way that they uniformly cover the entire designated area. These positions are considered as the starting points for the optimization algorithm so that the algorithm can begin the optimization process from an appropriate initial point.

Figure 1 shows the initial placement environment.

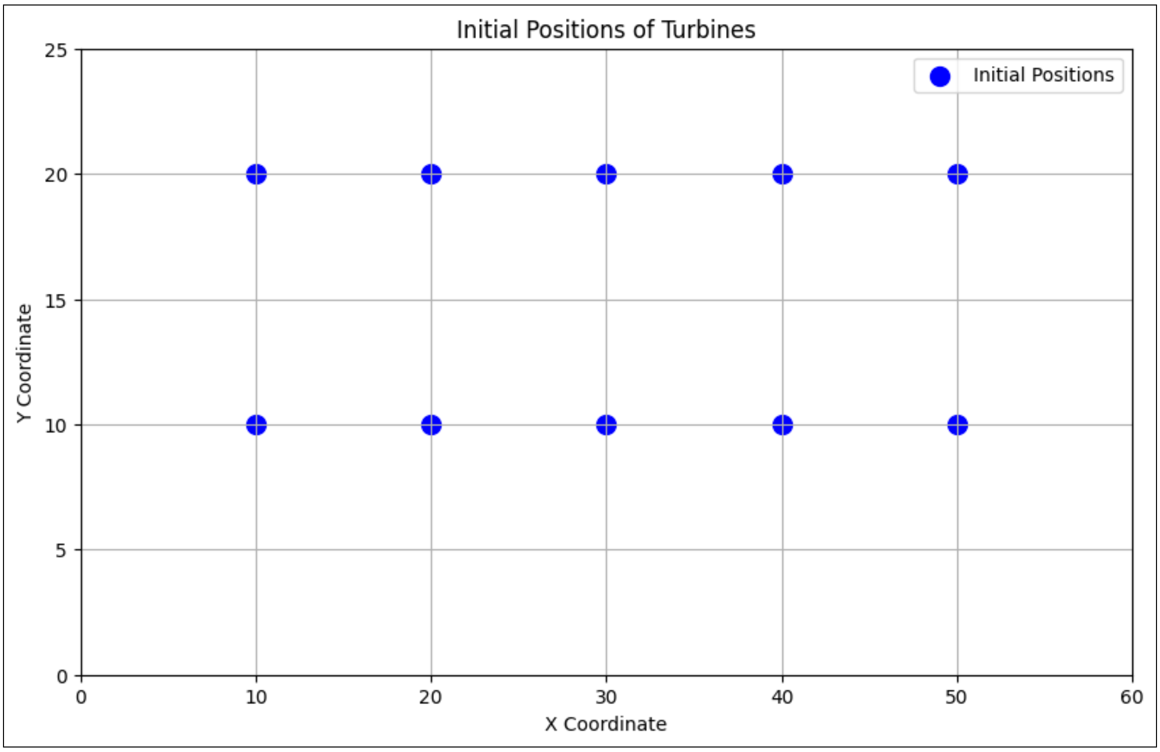

Fig 1: Initial location environment

In general, Table 1 shows the turbine coordinates before optimization.

Table 1: Turbine coordinates before optimization

Turbine number	X-coordinates	Y-coordinate
1	10	10
2	20	10
3	30	10
4	40	10
5	50	10
6	10	20
7	20	20
8	30	20
9	40	20
10	50	20

As mentioned earlier, in order to find the optimal positions of the turbines based on the stated conditions, the Grey Wolf Optimization algorithm was used with the specifications provided in Table 2.

Table 2: Specifications of the Gray Wolf Optimization Algorithm

Parameter	Amount
Initial population	100
Maximum repetitions	70
Number of turbines	10
Air density (ρ)	kg/m3
Sweeped area (A)	square meters
Objective function	Minimum interference and maximum energy
Stop condition	Reaching maximum repetitions (70 repetitions)

By executing the Grey Wolf Optimization algorithm, the positions of the turbines were improved throughout the algorithm iterations. Table 2 shows the optimal coordinates of the wind turbines after running the Grey Wolf Optimization algorithm. Furthermore, Figure 2 illustrates the optimal positions obtained by the Grey Wolf Optimization algorithm.

Table 3: Optimal coordinates of wind turbines

Turbine number	X-coordinates	Y-coordinate
1	0.00192344400	2.29285776
2	0.00000000	14.3952950
3	10.3456757	4.70663674
4	10.4582618	15.9089408
5	23.8039881	1.69307193
6	21.4635304	11.8919533
7	34.7454280	0.00000398318687
8	33.9225680	11.7608176
9	45.6939034	0.00000000
10	46.2270981	12.5487828

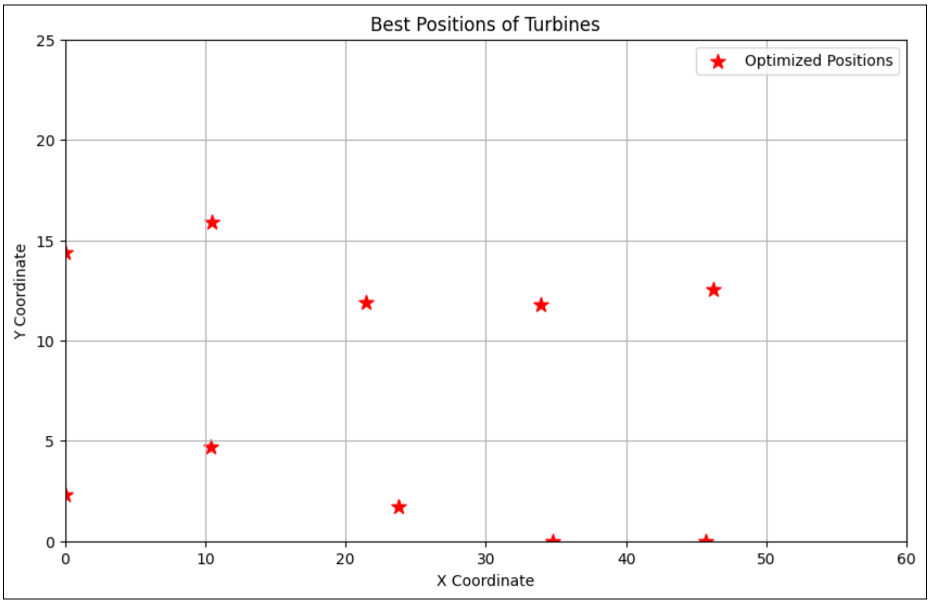

Fig 2: Optimal positions found by the Gray Wolf algorithm

After finding the optimal positions of the turbines, the evaluation criteria, including total produced energy and inter-turbine interference, were calculated in each iteration, and the results were analyzed as follows:

Amount of Produced Energy

In each iteration, the total produced energy of the turbines was calculated, and its variations over time were recorded. The graph in Figure 5-3 shows the changes in produced energy over the algorithm's iterations. The horizontal axis of Figure 3 represents the number of iterations, and the vertical axis indicates the amount of produced energy.

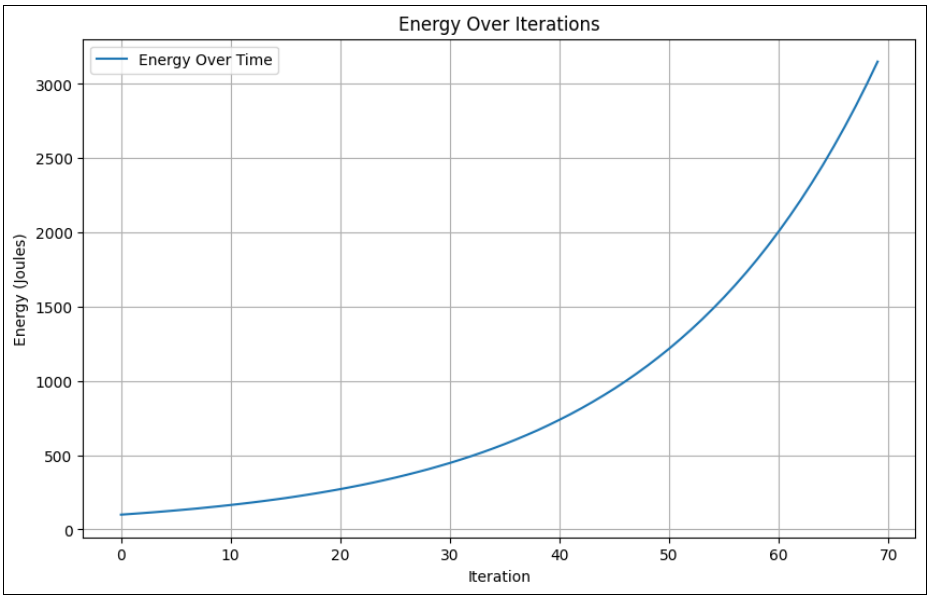

Fig 3: Changes in energy production during algorithm iterations

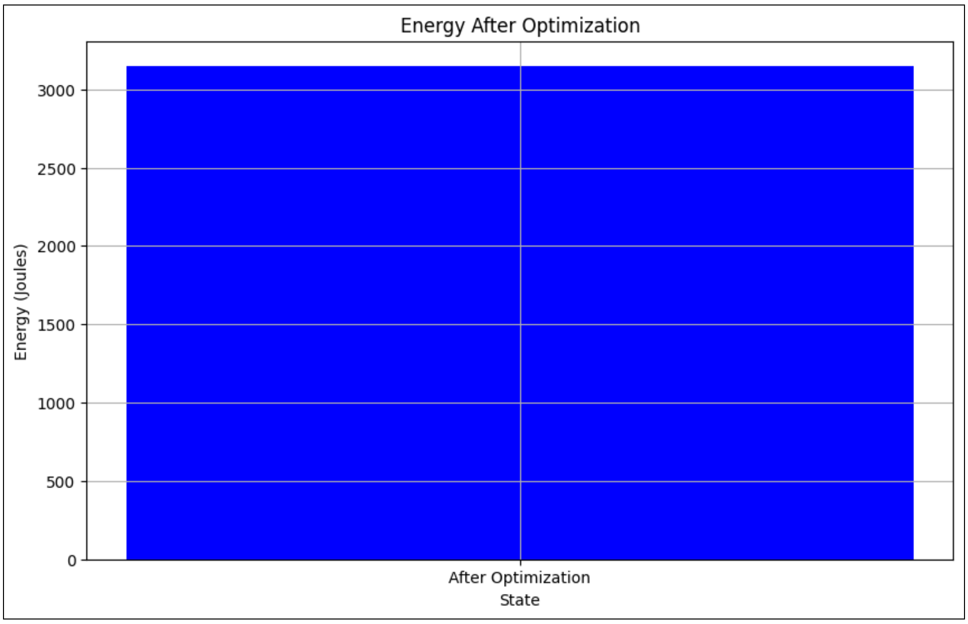

Fig 4: Total energy production for all turbines

Figure 3 shows that with the increase in the number of algorithm iterations, the amount of energy produced by the turbines gradually increases. This increase indicates an improvement in the positions of the turbines and their optimization throughout the algorithm's execution. This upward trend in produced energy confirms that the Grey Wolf Optimization algorithm is capable of effectively finding suitable positions for the turbines, resulting in the maximum possible energy production. As observed, with more iterations, the produced energy becomes more optimal, and the algorithm gradually moves toward the maximum energy output.

Interference between Turbines

Interference between turbines is considered a negative criterion, and the goal of the algorithm has been to reduce this interference. The graph in Figure 5 illustrates the changes in turbine interference throughout the algorithm's iterations.

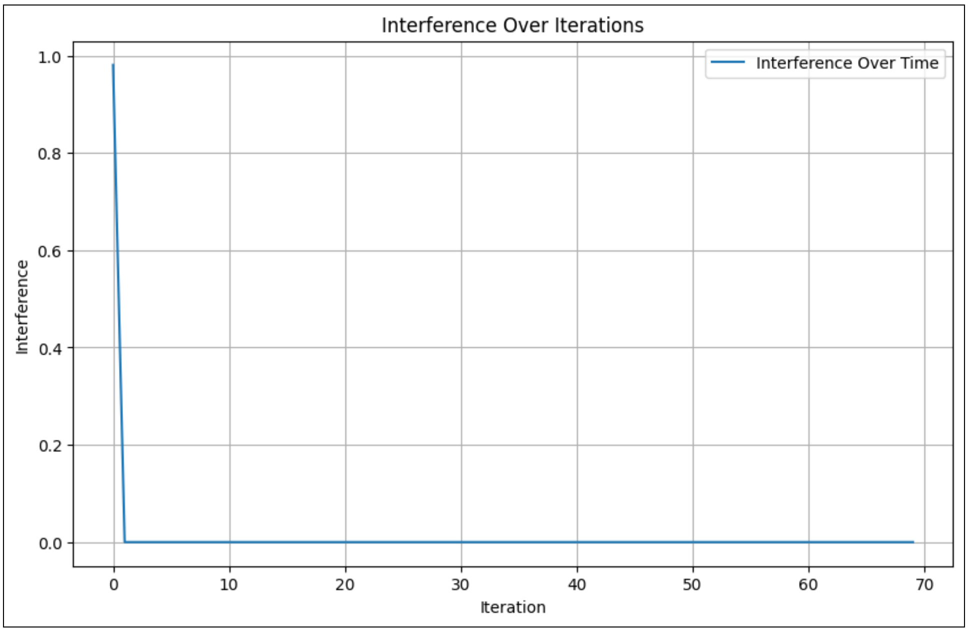

Fig 5: Diagram of changes in interference between turbines during algorithm iterations.

Figure 5 shows that the amount of interference between the turbines continuously decreases during the execution of the algorithm. This decrease indicates an improvement in the positions of the turbines in such a way that the interference between them is minimized. Reducing interference between turbines is highly important because lower interference means higher efficiency and more optimal performance of the turbines.

Overall, the obtained results demonstrate the effective performance of the Grey Wolf Optimization algorithm in optimizing the placement of wind turbines. The algorithm has successfully achieved desirable results by reducing interference between the turbines and increasing the produced energy. These results indicate the algorithm's efficiency in solving the optimal placement problem of wind turbines.

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